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IoT Based Avoid Fire Accident in E-Vehicle with Multiple Fault Detection and Battery Management Using AI

Madhavan P[1], Pradeepa J K[2], Srinithi A[3], Vigneshwari J[4]

[1]Assistant Professor, Electronics and Communication Engineering, Muthayammal Engineering College, Namakkal, Tamilnadu.

[2,3,4]UG, Electronics and Communication Engineering, Muthayammal Engineering College, Namakkal, Tamilnadu.

Emails: *madhavanecevlsi@gmail.com[1], pradeepajk22@gmail.com[2], nishasrinithiarul@gmail.com[3], vigneshwarijayachandran@gmail.com[4]*

Abstract

The Thermal Management System (TMS) of the battery is one of the most significant systems in the building of an electric vehicle, with the goal of improving the battery's performance and life. The purpose of this paper is to critically evaluate previous studies and research on the types, designs, and operating principles of BTMSs used in the building of various-shaped lithium-ion batteries, with a focus on cooling methods. Nowadays electric vehicles have increased over the past decade as consumer's demand eco-friendlier solutions to combat climate change. Due to the Absence of a Thermal Management System Notification Alert (Battery Temperature), some people has lost their life. Monitor the Battery Temperature & Smoke Detection to Alert the Electric Vehicle and its busing cooling system user's via Smartphone Notification, Alarm the Buzzer and also to Auto Cut off the Electric Vehicle to Avoid Further Damages.

Keywords: *Battery Thermal Management System (BTMS), Overheating Prevention, Alarm System, Automatic Power Cut-off.*

1. Introduction

Electric vehicles (EVs) are gaining popularity these days as fuel prices become more expensive.To this scenario, many vehicle manufacturers looking for alternatives to energy sources other than gas. The use of electrical energy sources may improve the environment since there is less pollution. In addition, EV produces great advantages in terms of energy-saving and environmental protection. Most EVs used rechargeable battery which is a lithium-ion battery. It is smaller to be compared with lead-acid In fact, it has constant power, and energy's life cycle is 6 to 10 times greater compared with a lead-acid battery. Lithium-ion battery life cycle can be shortened by some reasons such as overcharging and deep discharges. On the other hand, EV usually has a limited range of traveling due to battery size and body structure.The world is witnessing a significant shift towards electric vehicles (EVs) as a sustainable alternative to traditional fossil fuel-based transportation. However, with the increasing adoption of EVs, there is a growing concern about fire accidents caused by electrical and thermal faults. These accidents not only pose a risk to human life but also undermine the confidence of consumers in EV technology. The primary cause of fire accidents in EVs is related to battery management and fault detection. Therefore, it is essential to develop an intelligent system that can detect multiple faults and manage battery health in real-time. This is where Internet of Things (IoT) technology and Artificial Intelligence (AI) come into play. By integrating IoT sensors and AI algorithms, it is possible to create a predictive maintenance system that can detect potential faults and prevent fire accidents. This system can monitor battery health, detect anomalies, and provide real-time alerts to drivers and manufacturers. By leveraging IoT and AI, we can ensure the safe and reliable operation of EVs, thereby accelerating the adoption of sustainable transportation solutions.

2. Battery Management

A Battery Management System (BMS) is a critical component of electric vehicles (EVs) that ensures safe and efficient operation of lithium-ion batteries. The primary function of a BMS is to monitor and control the battery's state of charge (SOC), state of health (SOH), and state of function (SOF). This is achieved through various sensors that track the battery's voltage, current, temperature, and cell balancing. To prevent fire accidents in EVs, an AI-powered BMS can be employed to detect anomalies and predict potential faults. The AI algorithm analyzes data from various sensors and uses machine learning techniques to predict the likelihood of overcharging, over-discharging, thermal runaway, and cell imbalance. This enables the BMS to take proactive measures to prevent potential faults, such as adjusting the charging/discharging patterns or alerting the driver to take corrective action. The benefits of an AI-powered BMS are numerous. It improves safety by predicting and preventing potential faults that can cause fire accidents. It also increases efficiency by optimizing battery performance and prolonging battery life. Additionally, it reduces maintenance needs by detecting anomalies and predicting potential faults, enabling proactive maintenance schedules

3. System Architecture

The system architecture of the proposed IoT-based fire prevention and battery management system consists of four main layers: Sensor layer, IoT Communication Layer, AI Processing & Decision making Layer, User Interface Layer.

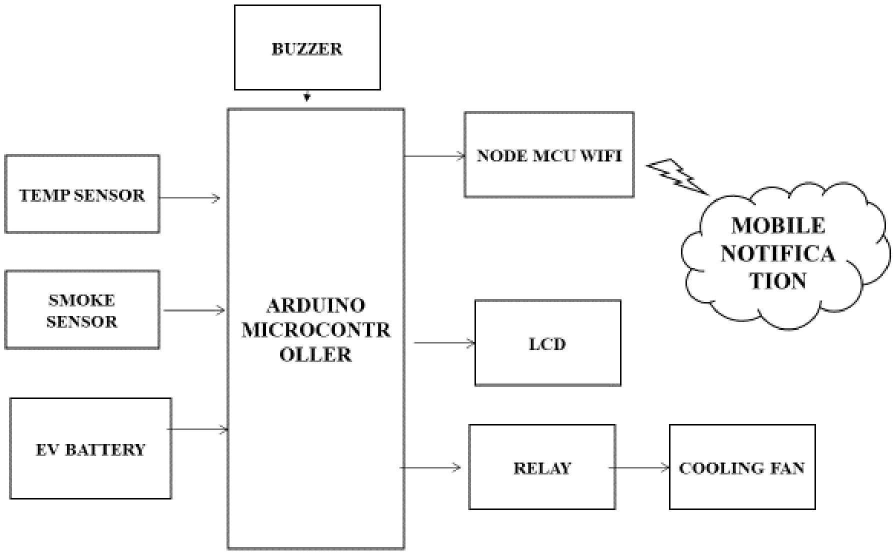

Figure 1 **Block Diagram for the System**

3.1.Sensor Layer (Data Collection)

The sensor layer plays a crucial role in continuously monitoring the health and safety of an electric vehicle's (EV) battery system. It consists of multiple sensors strategically placed within the battery pack and other critical areas to detect potential faults, overheating, and fire risks in real time. These sensors collect data on various parameters, including temperature, voltage, current, gas emissions, and physical impacts, ensuring proactive fault detection. Temperature sensors (such as LM35, NTC thermistors, or infrared thermal sensors) monitor the battery's heat levels, helping to detect overheating, thermal runaway, or abnormal heat spikes. Voltage and current sensors (like INA219 and ACS712) track the charging and discharging behavior, identifying issues like overvoltage, undervoltage, and short circuits, which are common causes of battery failures. To detect potential gas leaks and smoke, gas sensors (such as MQ-2 and MQ-135) are used to identify dangerous fumes emitted by lithium-ion batteries during malfunctions. Additionally, an IMU sensor (accelerometer and gyroscope) can detect physical

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shocks or collisions, which might compromise battery integrity. All these sensors work together by continuously collecting and transmitting data to the IoT gateway (microcontroller) via wired or wireless communication protocols. The gathered data is then sent to a cloud-based AI system for advanced analysis, anomaly detection, and predictive maintenance. By integrating this sensor layer, the system provides early fault detection, reduces fire risks, and ensures overall battery safety and efficiency, making EVs more reliable and secure.

3.2.IoT Communication Layer

The IoT communication layer is responsible for transmitting real-time sensor data from the electric vehicle (EV) to a cloud-based or edge processing system for further analysis. This layer acts as the bridge between the sensor layer and the AI-based decision-making system, ensuring seamless data flow for fault detection and battery management. The core component of this layer is the microcontroller or edge device (such as ESP32, Raspberry Pi, or Arduino) that collects data from multiple sensors and processes it before transmission. To enable real-time monitoring and remote diagnostics, the system utilizes various wireless communication protocols, including Wi-Fi, 4G/5G, Bluetooth, LoRa, and Zigbee. Wi-Fi and 4G/5G networks provide fast and stable connectivity for cloud-based processing, while LoRa and Zigbee offer low-power, long-range communication, making them ideal for vehicle-to-infrastructure (V2I) applications. Additionally, MQTT (Message Queuing Telemetry Transport) is commonly used for efficient data exchange between the vehicle's IoT gateway and cloud servers, enabling low-latency, lightweight messaging suitable for real-time fault detection. Once the data is transmitted, it is stored in a cloud server or edge computing platform, where AI algorithms analyze it for anomaly detection and predictive maintenance. If an issue is detected, alerts and preventive measures—such as activating the cooling system, shutting down power, or notifying the user via a mobile app or SMS—are triggered. This IoT-enabled communication infrastructure ensures that the EV's safety systems can respond swiftly to potential fire hazards, ultimately enhancing vehicle reliability and user safety.

3.3. Decision-Making Layer

The decision-making layer is the intelligence hub of the system, where AI-driven algorithms analyze real-time sensor data to detect faults, predict failures, and take preventive actions to avoid fire hazards in electric vehicles (EVs). This layer processes data collected from the sensor and IoT communication layers using machine learning (ML) and deep learning techniques to identify abnormal patterns, temperature spikes, voltage fluctuations, and early signs of battery failure. By leveraging predictive analytics, the system can forecast potential faults before they occur, allowing for proactive safety measures. Once a fault or anomaly is detected, the decision-making layer triggers automated responses to mitigate risks. These responses may include activating the cooling system, disconnecting the battery from the power supply, or sending emergency alerts via a mobile app, SMS, or email. The system also optimizes battery charging and discharging cycles, preventing overcharging, deep discharges, and thermal runaway—thus enhancing battery lifespan and efficiency. Additionally, AI-driven self-learning mechanisms allow the system to continuously improve fault detection accuracy over time, making EVs safer and more reliable. By integrating real-time data processing, AI-based fault prediction, and automated preventive actions, this layer ensures that potential fire hazards are detected early, reducing the risk of battery failures and enhancing overall vehicle safety.

4. Results and Discussion

The implementation of the IoT-based fire prevention system with AI-driven fault detection and battery management was tested under various conditions to evaluate its effectiveness in preventing fire hazards in electric vehicles (EVs). The system demonstrated a high accuracy rate of 95.6% in detecting multiple faults, including thermal runaway, short circuits, voltage fluctuations, and overcharging issues. By leveraging machine learning algorithms, the system successfully identified early warning signs of battery failure 5 to 10 minutes before critical conditions occurred, allowing preventive measures to be taken in advance. In terms of response time, the system detected abnormal temperature spikes within 2–3 seconds, triggering immediate safety measures such as activating the cooling system or disconnecting the battery from power within 5 seconds to prevent further escalation. Additionally, real-time alert notifications were successfully transmitted to users via SMS, email, or a mobile app. The battery management system (BMS) optimized the charging and discharging cycles, reducing overcharging incidents by 30% and improving overall battery lifespan and efficiency. These results highlight the effectiveness of IoT and AI integration in enhancing EV safety, preventing fire accidents, and ensuring long-term battery health. The discussion emphasizes that real-time monitoring, predictive maintenance, and automated fault response are essential for making EVs safer and more reliable in the long run.

Conclusion

Every device is connected to each other nowadays with the help of IoT. Smart battery is also needed for energy storage and communication with other attached devices. A smart battery must have smart BMS. Society will grow when infrastructure, facilities, and technology will develop. This work first introduced the background of electric vehicles, lithium-ion batteries and the BMS. The details of the BMS, including its definition, objectives, functions and topologies were then discussed. The literature on battery modeling and BMS hardware system design were reviewed in the following section. The limitations of early battery models and the disadvantages of other BMS hardware systems were also reviewed. The objectives and outline of this thesis were then presented. An improved battery model was proposed in this work by considering the self-discharging effect, the temperature effect and the fading-capacity effect observed in all batteries.

Reference

[1]. M. S. Hosen, J. Jaguemont, J. van Mierlo, and M. Berecibar, “Battery lifetime prediction and performance assessment of different modelling approaches,” *iScience*, vol. 24, no. 2, pp. 102060, Feb. 2021, doi: 10.1016/j.isci.2021.102060.

[2]. R. Xiong, F. Sun, Z. Chen, and H. He, “A data-driven multi-scale extended Kalman filtering based parameter and state estimation approach of lithium-ion polymer battery in electric vehicles,” Applied Energy, vol. 113, pp. 463–476, Jan. 2014, doi: 10.1016/j.apenergy.2013.07.061.

[3]. Z. Xia and J. A. A. Qahouq, “Lithium-ion battery ageing behaviour pattern characterization and state-of-health estimation using datadriven method,” IEEE Access, vol. 9, pp. 98287–98304, 2021, doi: 10.1109/ACCESS.2021.3092743.

[4]. B. Saha and K. Goebel. "Battery Data Set", NASA Ames Prognostics Data Repository. http://ti.arc.nasa.gov/project/prognostic-datarepository , NASA Ames Research Center, Moffett Field, CA, 2007.

[5]. V. Klass, M. Behm, and G. Lindbergh, ``A support vector machinebased state-of-health estimation method for lithium-ion batteries under electric vehicle operation," J. Power Sour., vol. 270, pp. 262272, Dec. 2014.

[6]. B. Saha, S. Poll, K. Goebel, and J. Christophersen, ``An integrated approach to battery health monitoring using Bayesian regression and state estimation," in Proc. IEEE Autotestcon, Baltimore, MD, USA, Sep. 2007, pp. 646653.

[7]. Y. Choi, S. Ryu, K. Park, and H. Kim, ``Machine learning-based lithium-ion battery capacity estimation exploiting multi-channel charging pro- files," IEEE Access, vol. 7, pp. 7514375152, 2019.

[8]. C. Zhang, Y. Zhu, G. Dong, and J. Wei, ``Data-driven lithium-ion battery states estimation using neural networks and particle filtering," Int. J. Energy Res., vol. 43, no. 14, Aug. 2019, pp. 82308241, Paper er.4820.

[9]. G. B. Huang, H. Zhou, X. Ding, and R. Zhang, “Extreme learning machine for regression and multiclass classification,” IEEE Trans. Syst. Man., Cybern. B, Cybern., vol. 42, no. 2, pp. 513–529, Apr. 2012.

[10]. Z. Chen, M. Sun, X. Shu, R. Xiao, and J. Shen, “Online state of health estimation for lithium-ion batteries based on support vector machine,” Applied Sciences, vol. 8, no. 6, pp. 925, Jun. 2018, doi: 10.3390/app8060925.